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Adaptive on-line prediction of the available power of lithium-ion batteries

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HIGHLIGHTS

- Model-based power prediction algorithm for lithium-ion battery packs.
- Non-linear model includes current dependency of battery resistance.
- All parameters are fully adaptable on-line to the present state of the battery.
- Optimized algorithm ensures its real-time capability.

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ABSTRACT

In this paper a new approach for prediction of the available power of a lithium-ion battery pack is presented. It is based on a nonlinear battery model that includes current dependency of the battery resistance. It results in an accurate power prediction not only at room temperature, but also at lower temperatures at which the current dependency is substantial. The used model parameters are fully adaptable on-line to the given state of the battery (state of charge, state of health, temperature). This on-line adaption in combination with an explicit consideration of differences between characteristics of individual cells in a battery pack ensures an accurate power prediction under all possible conditions. The proposed trade-off between the number of used cell parameters and the total accuracy as well as the optimized algorithm results in a real-time capability of the method, which is demonstrated on a low-cost 16 bit microcontroller. The verification tests performed on a software-in-the-loop test bench system with four 40 Ah lithium-ion cells show promising results.

1. Introduction

This paper presents results of a study aiming at the development of battery monitoring algorithms for lithium-ion battery packs that are both long-term stable and self-adaptable to the state of health of the battery. Lithium-ion battery packs are always equipped with a battery management system (BMS). The BMS consists of hardware and software for battery monitoring including, among others, algorithms determining battery states. The battery states of interest are state of charge (SoC), state of health (SoH) and some states of function (SoF). State of function is a figure of merit that describes the capability of the battery to perform a certain task in a given application.

In many applications batteries have not only to deliver certain amount of energy to the loads during operation, but also to provide certain power in various situations. The power capability of the battery can be limited by the voltage, current, SoC and temperature ranges approved for the safe operation. Since batteries are complex electrochemical devices, their power capability depends on a variety of internal and external conditions: temperature, SoC, previous load history. It also changes significantly over the battery lifetime due to aging.

For the energy management system (EMS) in the application it can be essential to know the power of the battery available in the next short time period. Examples of such application are the battery electrical vehicles (BEV) and hybrid electrical vehicles (HEV). In

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these applications the energy management has to know which maximal power can be applied to the battery by charging or discharging it in the next 1–20 s. Therefore, the available power can be defined as an additional state of the battery – state of available power (SoAP) – and its prediction has to be performed by the BMS.

In this paper a method for an accurate, on-line and to the SoH of the battery adaptive prediction of the available power of lithium-ion batteries is presented. This work is organized as follows. Section 2 gives an overview over existing techniques; their advantages and disadvantages are discussed and the need for a new method is derived. In Section 3 different definitions of power prediction and respective reference cases are discussed. Section 4 describes the proposed method for the prediction of the available power including consideration of differences between characteristics of individual cells in a battery pack. In Section 5 the software-in-the-loop (SIL) setup is described. It is used for verification tests presented and discussed in Section 6. Finally, Section 7 gives a conclusion.

2. Existing techniques for the prediction of the available power

Existing techniques for the prediction of the available power can be divided into two groups: methods based on a characteristic map and methods based on a dynamic battery model.

First group of methods uses the static interdependence between the available power of the battery, the battery states (for example SoC, temperature, voltage) and power pulse parameters (for example duration of the power pulse). These dependencies are stored in form of a characteristic map [1–3] in a non-volatile memory of BMS and used for power prediction. The initial parameterization of the characteristic map can be performed in the laboratory. Test procedures for battery pulse power characterization as defined in various manuals and standards [4–7] can be employed. Since battery characteristics change over the time due to aging, on-line adaption of the characteristic map is required. For this the predicted and the measured available power are compared. The difference between them is used to adapt the respective reference point in the characteristic map. As a result, the future prediction of the available power in this operating point is more accurate.

The main advantage of this first group of methods is their simplicity and straight forward implementation. The first disadvantage of these methods is that only static battery characteristics are considered. If very dynamic load is applied to the battery in the application, then the available power may depend very strong on the previous load history because of various polarization overvoltages in the battery. Since these overvoltages are not taken into account, the accuracy of power prediction is very low. The other disadvantage is attendant on the adaption technique. If the maximal available power has to be predicted, then the respective characteristic map can be adapted only when this maximal power is in reality applied to the battery. Otherwise the comparison between the prediction and the measurement is not possible and, in consequence, the adaption cannot be performed. It limits the adaption rate in applications where the maximal power is applied to the battery very infrequently so that there are only very few possibilities for the adaption during normal operation. The third disadvantage is the need for storing the multidimensional characteristic map. It requires significant amount of non-volatile memory which may be not available on a low-cost target microcontroller. This problem can be overcome by an approximation of the characteristic map with one or more empirical functions [1,8]. In this case only few parameters of these functions have to be stored in the memory.

The second group of methods is based on a dynamic battery model. If the behavior of the battery can be modeled very accurate, then the available power can be also predicted very accurate. The existing methods [9–16] differ mainly in the type of used models. The important feature that must be implemented additionally is the on-line adaption of model parameters to the present state of health of the battery. An overview of adaption techniques can be found in Ref. [17]. The need for on-line parameter adaption prevents using very complex battery models, but they must be chosen to be sufficient for an accurate power prediction.

Generally, the model based prediction of the available power is the most promising approach. It considers accurate the dynamic behavior of the battery and therefore can be applied by very dynamic loads. Unfortunately, battery models employed by other authors do not consider one important aspect that is the current dependency of the battery resistance. As shown in Refs. [17,18], the current dependency can be neglected for new cells and at room temperatures but it is considerable at lower temperatures as well as for aged cells. The promising results shown by other authors [9,12–14] are always obtained at room temperatures and by applying the proposed algorithms on new cells. However, the prediction of the available power plays higher role at lower temperatures and for aged batteries because the battery will rather reach the power limit at these conditions. Therefore, algorithms must able to deliver accurate results and must be verified at these unfavorable conditions.

The other aspect that must be considered, when the model based approach is used, is that in a battery pack a large number of cells are connected in series. They might have slightly different characteristics and different SoC, especially in an aged state. As a result, the available power of each single cell can be different and the available power of the total battery pack must be calculated considering each individual cell. Some authors [9,12] propose using the battery model separately for each cell in a battery pack. The disadvantage is that it requires high computing power because lots of model instances and their parameters must be calculated. Other authors do not propose any solution for the consideration of single cell characteristics.

It can be concluded that a new method for prediction of the available power is required. It must be preferably based on a dynamic battery model to keep all advantages of model based approaches. It must also be adaptable to the state of health of the battery and consider two aspects very accurate: the current dependency of the battery resistance and differences between characteristics of individual cells in a battery pack. Furthermore, for a practical usage it must be proven to be capable running on a low-cost target hardware.

3. Different definitions of power prediction

Before the proposed method for power prediction is presented, the definition of the available power and the definition of its prediction must be considered carefully.

As mentioned in the Introduction, the available power is limited by the safe operating area (SOA) of the battery. The SOA is defined by temperature, voltage, current and SoC limits. At this point it is important to remember that not the total battery voltage, but the voltage of each individual cell in a battery pack must be kept in certain limits because of safety reasons. For power prediction with a short forecast period (up to some 10 s) the changes of the battery temperature and SoC play rather a secondary role since they are very slowly. In most cases battery current and voltage limits are in practice the limiting factors for the available power. Therefore, the currently available power can be defined as a maximal power that can be applied to the battery in a given moment, so that the battery current or voltage reaches exactly one of the predefined limits, but

neither current nor voltage exceed them. The definition of the prediction of the available power is not that unequivocal. The reason is that the power available in the next time period depends significantly on what is going to happen in this next period to the battery load. Battery load in the application typically cannot be predicted. Therefore to predict the available power a reference case must be considered. Typical reference cases are charging or discharging the battery with a constant current, a constant voltage or a constant power. It is up to the needs in the particular application which reference case must be used. All reference cases are rather artificial events that most likely never occur during normal battery operation. For example constant current event implies instantaneous current change at the beginning of the current pulse, but in a real application the current always has a finite rate of change. The reference case of constant current pulse can be then considered as a worst case scenario.

In this work the constant current pulse is used as a reference case for the prediction of the available power because of three reasons:

- It is practically often used because power electronic devices, which connect the battery and the load (for example electrical motor), can be easily regulated for a constant current.
- It is mainly used by other authors [11–14] and therefore permits comparison of different techniques.
- It is very close to the other practically useful reference case – discharging or charging the battery with constant power – because the voltage change during a constant current pulse is rather small. Furthermore, as exemplarily shown in Section 6, power predicted for the constant current case can be practically applied by a constant power load at tolerable inaccuracy but by sufficient lower demand on computing power.

4. Proposed method for the prediction of the available power

In this section a new method for the prediction of the available power of lithium-ion battery is presented. The power prediction for one single cell based on an equivalent circuit model (ECM) is described in Section 4.1. In Section 4.2 the efficient technique for the determination of the total available power of a battery pack under consideration of differences between characteristics of individual cells connected in series is presented. Section 4.3 describes algorithms for the determination of parameters of individual cells in a battery pack. These parameters are needed for power prediction.

4.1. Power prediction for one single cell

As a basis for power prediction the equivalent circuit model of the cell shown in Fig. 1 is used [17]. The voltage V_{OCV} in this ECM represents the open circuit voltage (OCV) of the battery cell. The resistance R_0 corresponds to the internal resistance of the battery at

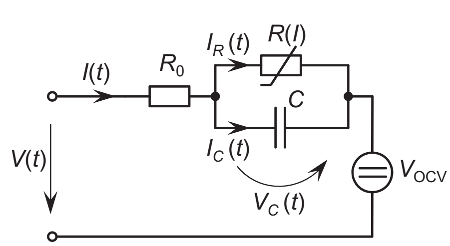

Fig. 1. The equivalent circuit model (ECM) of a battery used as a basis for power prediction.

high frequencies and is linear (current independent). The capacitance C corresponds to the double layer capacity of the battery and is also considered as current independent. The resistance $R(I)$ corresponds mainly to the charge transfer reaction. In contrast to other parameters it is highly nonlinear and can be modeled as [17],[1]:

$$R(I) = R_1 \cdot \left(\frac{\ln\left(k_I \cdot I + \sqrt{(k_I \cdot I)^2 + 1}\right)}{k_I \cdot I} \right) \tag{1}$$

R_1 [Ω] is the resistance at $I = 0$ A. k_I [A^{-1}] is a parameter that describes the current dependency of the resistance.

All parameters (R_0, C, R_1 and k_I) change for different temperatures, SoC and SoH of the battery.

As mentioned in Section 3, the charging or discharging the battery with constant current is taken as a reference case for the prediction of the available power in this work. The available power for charging the battery is then limited by the maximal charge current I_{max} or the maximal cell voltage V_{max} at the end of the charging pulse with duration Δt. The available power for discharging the battery is limited by the minimal (negative) discharge current I_{min} or the minimal cell voltage V_{min} at the end of the discharging pulse. These four possible cases are shown in Fig. 2. The limits I_{max}, I_{min}, V_{max} and V_{min} are predefined in accordance to the manufacturer specification of the given cell type. The current limits (I_{max}, I_{min}) are eventually temperature-dependent to prevent, for example, lithium plating.

The prediction of the maximal available power is performed directly before the respective current pulse at time $t = 0$. For this the following cell parameters and initial conditions must be known:

1) Parameters of the cell model (Fig. 1): R_0, R_1, C and k_I. These parameters can be calculated on-line using the technique presented in our previous work [17] and summarized in Section 4.3.
2) The initial voltage $V_C(t = 0)$ on the capacitance C. This is the present voltage on the capacitance at the time of power prediction. Its determination is also the part of the calculation of battery parameters presented in our previous work [17].
3) The open circuit voltage[2] $V_{OCV}(t = 0)$ at the beginning of the constant current pulse. It can be calculated using measured battery current $I_{meas}(t = 0)$ and voltage $V_{meas}(t = 0)$ directly before the current pulse according to the ECM in Fig. 1:

$$\begin{aligned} V_{OCV}(t = 0) = V_{meas}(t = 0) - I_{meas}(t = 0) \cdot R_0 \\ - V_C(t = 0) \end{aligned} \tag{2}$$

Using these parameters and initial conditions the following steps can be performed to predict the maximal available charging or discharging power ($P_{ch}(\Delta t)$, $P_{disch}(\Delta t)$):

[1] In Ref. [17] the resistance R is modeled depending on the current I_R through this resistance: $R(I_R)$. In this work it is modeled depending on the total battery current I. It causes some additional inaccuracies in transient cases, but does not cause any error in steady state condition when battery current is constant. The advantage is that using this simplification the value of the resistance $R(I)$ remains constant during constant current pulse that simplifies significantly the calculation of the available power.

[2] Actually, this open circuit voltage is not only the electromotive force of the cell, but may additionally include other overvoltages (e.g. diffusion overvoltage) that changes slowly relative to the time constant of the RC element in Fig. 1. Therefore, it cannot be determined with a sufficient accuracy only by considering the battery SoC. The proposed method is more appropriate in this case.

1) Calculation of the maximum allowable charge current I_{ch} and the minimum allowable discharge current I_{disch}. The condition for this calculation is that the cell voltage $V(\Delta t)$ at the end of the constant current pulse reaches exactly its limit V_{max} by charging (Fig. 2a) or V_{min} by discharging (Fig. 2c). An iterative calculation is required as described later in this section. In this step also the current limits (I_{max}, I_{min}) are considered so that the calculated currents are limited: $I_{ch} \le I_{max}$ and $I_{disch} \ge I_{min}$.
2) Calculation of the battery voltage at the end of the charging ($V_{ch}(\Delta t)$) or discharging ($V_{disch}(\Delta t)$) pulse. Thereby the ECM in Fig. 1 and currents I_{ch}, I_{disch} calculated in the first step are used:

$$\begin{aligned} V_{ch}(\Delta t) =& V_{OCV}(t=0) + R_0 \cdot I_{ch} \\ &+ R(I_{ch}) \cdot I_{ch} \cdot \left(1 - \exp\left(\frac{-\Delta t}{R(I_{ch}) \cdot C}\right)\right) \\ &+ V_C(t=0) \cdot \exp\left(\frac{-\Delta t}{R(I_{ch}) \cdot C}\right) \\ &+ K_{OCV}(\mathrm{SoC}) \cdot \Delta t \cdot I_{ch} \end{aligned} \tag{3a}$$

$$\begin{aligned} V_{disch}(\Delta t) =& V_{OCV}(t=0) + R_0 \cdot I_{disch} \\ &+ R(I_{disch}) \cdot I_{disch} \cdot \left(1 - \exp\left(\frac{-\Delta t}{R(I_{disch}) \cdot C}\right)\right) \\ &+ V_C(t=0) \cdot \exp\left(\frac{-\Delta t}{R(I_{disch}) \cdot C}\right) \\ &+ K_{OCV}(\mathrm{SoC}) \cdot \Delta t \cdot I_{disch} \end{aligned} \tag{3b}$$

$R(I_{ch})$ and $R(I_{disch})$ are calculated according to Eq. (1). $K_{OCV}(\mathrm{SoC})$ [V A^{-1} s^{-1}] is the change of the open circuit voltage per discharged or charged ampere second. It can be parameterized offline for a given cell type.

3) Calculation of the available charging and discharging power using currents and voltages calculated in first two steps:

$$P_{ch}(\Delta t) = V_{ch}(\Delta t) \cdot I_{ch} \tag{4a}$$

$$P_{disch}(\Delta t) = V_{disch}(\Delta t) \cdot I_{disch} \tag{4b}$$

For the calculation of the maximum allowable charge current I_{ch} or minimum allowable discharge current I_{disch} that lead respectively to the battery voltage V_{max} or V_{min} at the end of charging or discharging pulse (step 1), the following equation must be solved:

$$\begin{aligned} V_{lim} =& V_{OCV}(t=0) + R_0 \cdot I_{lim} + R(I_{lim}) \\ &\cdot I_{lim} \cdot \left(1 - \exp\left(\frac{-\Delta t}{R(I_{lim}) \cdot C}\right)\right) \\ &+ V_C(t=0) \cdot \exp\left(\frac{-\Delta t}{R(I_{lim}) \cdot C}\right) + K_{OCV}(\mathrm{SoC}) \cdot \Delta t \cdot I_{lim} \end{aligned} \tag{5}$$

$V_{lim} = V_{max}$ and $I_{lim} = I_{ch}$ for the case of charging; $V_{lim} = V_{min}$ and $I_{lim} = I_{disch}$ for the case of discharging.

No direct solution exists for this problem. Therefore an iterative search must be applied. The Newton–Raphson method [19] is sufficient for this purpose. It consists in applying the following iterative equation:

$$I_j = I_{j-1} - f(I_{j-1}) / f'(I_{j-1}) \tag{6}$$

I_j is the approximation of the desired solution for the current I_{lim} at present iteration step j; I_{j-1} is the approximation of the desired solution for the current I_{lim} at previous iteration step $j-1$; $f(I_{j-1})$ and $f'(I_{j-1})$ are the function obtained from Eq. (5) and its derivative:

$$\begin{aligned} f(I_{j-1}) =& V_{OCV}(t=0) + R_0 \cdot I_{j-1} + R(I_{j-1}) \cdot I_{j-1} \cdot (1 - K_{\exp,j-1}) \\ &+ V_C(t=0) \cdot K_{\exp,j-1} + K_{OCV}(\mathrm{SoC}) \cdot \Delta t \cdot I_{j-1} - V_{lim} \end{aligned} \tag{7}$$

$$\begin{aligned} f'(I_{j-1}) =& R_0 + K_{OCV}(\mathrm{SoC}) \cdot \Delta t + \left(R(I_{j-1}) + I_{j-1} \cdot \left.\frac{\mathrm{d}R(I)}{\mathrm{d}I}\right|_{I=I_{j-1}} \right) \\ &\cdot (1 - K_{\exp,j-1}) + K_{\exp,j-1} \cdot \Delta t \cdot \left.\frac{\mathrm{d}R(I)}{\mathrm{d}I}\right|_{I=I_{j-1}} \Big/ (C \cdot R(I_{j-1})) \\ &\cdot \left(\frac{V_C(t=0)}{R(I_{j-1})} - I_{j-1} \right) \end{aligned} \tag{8}$$

with

$$K_{\exp,j-1} = \exp\left(\frac{-\Delta t}{R(I_{j-1}) \cdot C}\right) \tag{9}$$

and

$$\begin{aligned} \left.\frac{\mathrm{d}R(I)}{\mathrm{d}I}\right|_{I=I_{j-1}} =& R_1 \cdot \left(\frac{1}{I_{j-1} \cdot \sqrt{(k_I \cdot I_{j-1})^2 + 1}} \right. \\ &\left. - \frac{\ln\left(k_I \cdot I_{j-1} + \sqrt{(k_I \cdot I_{j-1})^2 + 1}\right)}{k_I \cdot I_{j-1}^2} \right) \end{aligned} \tag{10}$$

The total iteration algorithm for the calculation of the maximum allowable discharge current I_{disch} is shown in Fig. 3. The calculation begins with initialization (step 1). The iteration counter j is set to zero and the current estimation I_j is set to its initial value $I_{initial}$. The initial value can be, for example, the maximum allowable discharge current calculated in the previous sample step $k-1$ of the total power prediction algorithm, which is the best initial estimation. Based on this value the voltage of the battery at the end of discharge pulse $V_{disch}(\Delta t)$ is predicted according to Eq. (3) with $I_{disch} = I_j$ (step 2). If the predicted voltage $V_{disch}(\Delta t)$ deviates from the battery voltage limit V_{min} by a value that is smaller than the predefined maximal deviation[3] ΔV_{max} (step 3), then the solution has been found: $I_{disch} = I_j$ (step 4). Otherwise, the next iteration step is initialized by calculation of the new estimated current I_j according to Eq. (6) (step 5). The voltage $V_{disch}(\Delta t)$ is calculated again using the current estimation I_j (step 6). If this estimation I_j used for voltage prediction is already lower than discharge current limit I_{min}, but the predicted voltage is still higher than the voltage limit V_{min} (step 7), then the available power is limited not by the voltage but by the current. In this case the desired solution is $I_{disch} = I_{min}$ (step 8). Otherwise the iteration is continued by checking the condition in step 3.

The maximum allowable charge current I_{ch} can be calculated applying the same methodology.

The required number of iterations depends mainly on the value chosen for the initial current $I_{initial}$. Typically no more than 4

[3] It makes sense to stop iterations when the deviation between the predicted voltage and the voltage limit is smaller than the absolute accuracy of the voltage measurement. In this work $\Delta V_{max} = 5$ mV is used.

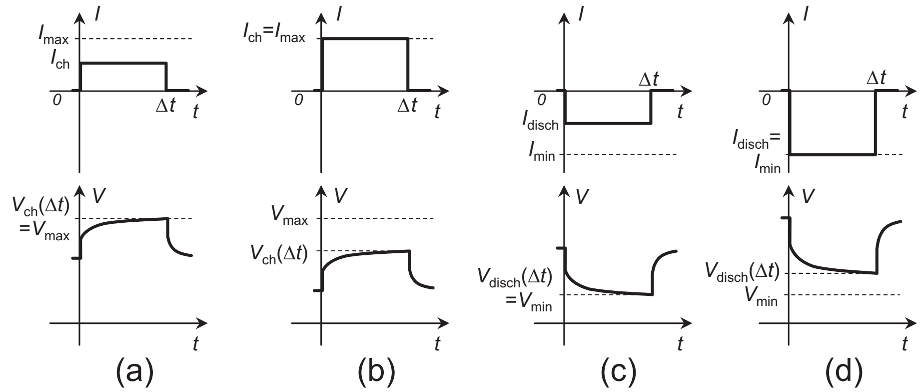

Fig. 2. Four different cases for limiting the battery power in case of constant current charging or discharging: (a) voltage reaches its limit (V_{max}) at the end of the charging pulse with current $I_{ch} < I_{max}$; (b) charging with the maximal current I_{max} without reaching the voltage limit; (c) voltage reaches its limit (V_{min}) at the end of the discharging pulse with current $I_{disch} > I_{min}$; (d) discharging with the minimal (negative) current I_{min} without reaching the voltage limit.

iterations are needed even if an absolutely inappropriate initial current is chosen. If $I_{initial}$ is taken as a result of the calculation in the previous time step $k-1$, then only one iteration is needed because the maximum allowable currents do not change in a fast manner.

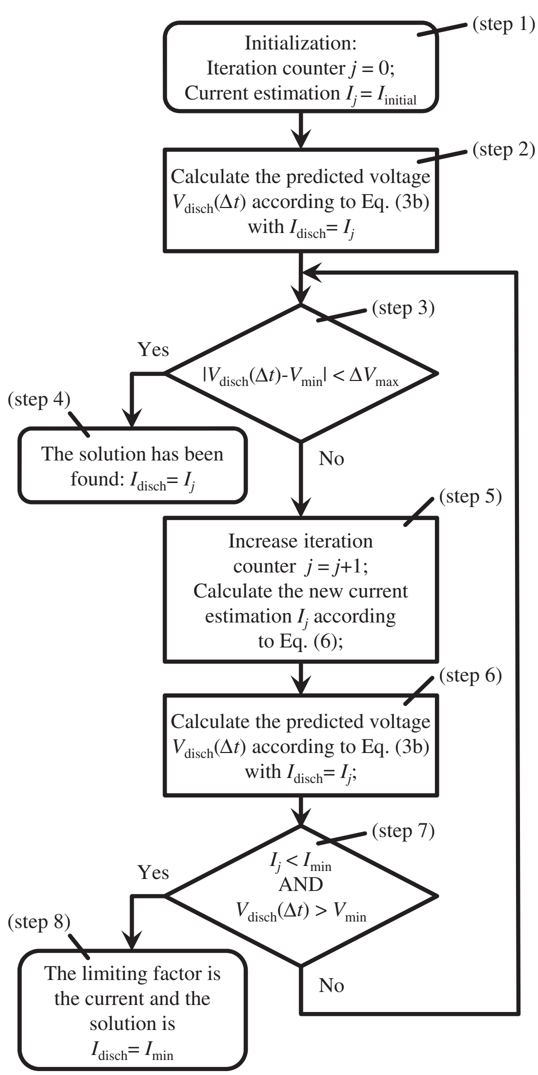

Fig. 3. The algorithm for calculation of the maximum allowable discharge current I_{disch}.

After the maximum allowable charge and minimum allowable discharge currents have been calculated, the battery voltage and the battery power can be predicted as described above (Eqs. (3) and (4)).

4.2. Determination of the total available power of a battery pack under consideration of differences between characteristics of individual cells

In Section 4.1 the method for the prediction of the available power of one single cell is presented. However, in a lithium-ion battery pack typically many cells (up to some hundred) are connected in series. The available power of the total battery pack is therefore limited by the "weakest" cell. The "weakest" is the cell that first reaches the predefined voltage or current limit by charging or discharging the battery.

If all cells in the battery pack are considered having completely different characteristics and different conditions, then it is not possible to determine which cell is the "weakest" without calculating the available power for each individual cell. In this case a straight-forward method must be applied. It calculates the maximum allowable charge and minimum allowable discharge current for each cell, predicts the voltage of each single cell and then calculates the available power. This method is presented in Section 4.2.1.

The straight-forward method requires substantial computing power and consumes lots of memory to store parameters of each individual cell. Neither high computing power nor high volume of memory can be available on a low-cost microcontroller used in BMS. Therefore, another approach is proposed in this work. The idea is to reduce the total number of cell parameters assuming that all cells are very similar in their characteristics. Only the present OCV and the cell resistance are considered being different for different cells. These differences may imply different SoC, SoH and different temperatures. Best candidates to be the "weakest" cells are the cell with the highest resistance and the cell with the highest OCV (for charging power) or lowest OCV (for discharging power). These cells are considered first. Then only a reduced number of further cells must be considered too. These cells must have a certain combination of the OCV and the resistance that may lead to the lowest (for discharging power) or highest (for charging power) voltage under load. For discharge power that are:

- cells with resistance higher than the resistance of the cell with the lowest OCV and

- cells with OCV lower than the OCV of the cell with the highest resistance.

For charge power that are:

- cells with resistance higher than the resistance of the cell with the highest OCV and
- cells with the OCV higher than the OCV of the cell with the highest resistance.

Cells that do not satisfy these criteria are definitely not classified as "weak" regarding available power. Therefore they are excluded from further considerations. This method requires significantly lower computing power and has less memory consumption than the straight-forward method because of this preselection. It is presented in Section 4.2.2.

4.2.1. The straight-forward method

The straight-forward approach for calculating the available power of the total battery pack consists of six steps described in the following:

1) For each cell n ($n = 1\ldots N$, N − number of cells connected in series) current limits $I_{\max}^{(n)}$ and $I_{\min}^{(n)}$ based on the battery specification and eventually on present conditions (e.g. temperature) are defined.
2) The total current limits for the entire battery pack are calculated:

$$I_{\max} = \min_{n=1\ldots N}\left(I_{\max}^{(n)}\right) \tag{11a}$$

$$I_{\min} = \max_{n=1\ldots N}\left(I_{\min}^{(n)}\right) \tag{11b}$$

3) For each cell n the predefined voltage limits ($V_{\max}$, $V_{\min}$), cell parameters ($R_0^{(n)}, R_1^{(n)}, C^{(n)}, k_I^{(n)}$) according to the ECM in Fig. 1 and the initial conditions ($V_C^{(n)}(t=0), V_{OCV}^{(n)}(t=0)$) are taken into account: the maximum allowable charge current and the minimum allowable discharge current ($I_{ch}^{(n)}, I_{disch}^{(n)}$) are calculated applying the algorithm presented in Section 4.1.
4) The total maximum allowable charge and the total minimum allowable discharge currents for the whole battery pack are calculated:

$$I_{ch} = \min_{n=1\ldots N}\left(I_{ch}^{(n)}\right) \tag{12a}$$

$$I_{disch} = \max_{n=1\ldots N}\left(I_{disch}^{(n)}\right) \tag{12b}$$

5) For each cell n the voltage at the end of the charging pulse and at the end of the discharging current pulse ($V_{ch}^{(n)}(\Delta t), V_{disch}^{(n)}(\Delta t)$) are predicted according to Eq. (3). Subsequently the total battery pack voltages are calculated:

$$V_{ch}(\Delta t) = \sum_{n=1}^{N} V_{ch}^{(n)}(\Delta t) \tag{13a}$$

$$V_{disch}(\Delta t) = \sum_{n=1}^{N} V_{disch}^{(n)}(\Delta t) \tag{13b}$$

6) The total charging and discharging power are calculated according to Eq. (4).

The advantage of this approach is that the characteristics of individual cells are considered accurate. It results in an accurate power prediction. However, the accuracy is achieved at the expense of computing power because this algorithm requires that parameters of all individual cells are known. For this the complex algorithm for the on-line determination of cell parameters must be applied separately for each cell in a battery pack.

4.2.2. The method optimized regarding computing power

In practice all cells in a battery pack have very similar SoC, SoH and temperature. Therefore it can be expected that the variation among parameters of single cells is rather small [20]. In particular the following assumptions can be made:

1) The current dependency is the same for each cell: $k_I^{(n)} = k_I$.
2) The dynamic of each cell, defined as the time constant of the RC-element ($\tau^{(n)} = R^{(n)}(I)\cdot C^{(n)}$), is the same: $\tau^{(n)} = \tau$.
3) The resistances $R_0^{(n)}$ and $R_1^{(n)}$ of each individual cell are proportional to the average cell resistance R_0 and R_1 respectively. The proportional coefficient $k_R^{(n)}$ varies for different cells, but is the same for $R_0^{(n)}$ and $R_1^{(n)}$:

$$R_0^{(n)} = k_R^{(n)}\cdot R_0 \tag{14a}$$

$$R_1^{(n)} = k_R^{(n)}\cdot R_1 \tag{14b}$$

This proportional coefficient can be described as a relative resistance of each single cell related to an average cell resistance in a battery pack.

The result of these assumptions is that only three differences among all cells in a battery pack must be considered: their relative resistances $k_R^{(n)}$, their initial open circuit voltages $V_{OCV}^{(n)}(t=0)$ and their initial voltages $V_C^{(n)}(t=0)$ on the capacitance C (Fig. 1) directly before the current pulse. The initial open circuit voltage can be calculated for each cell n according to Eq. (2):

$$V_{OCV}^{(n)}(t=0) = V_{meas}^{(n)}(t=0) - I_{meas}(t=0)\cdot R_0\cdot k_R^{(n)} - V_C^{(n)}(t=0) \tag{15}$$

$V_{meas}^{(n)}(t=0)$ and $I_{meas}(t=0)$ are the voltage of the cell n and the battery current measured directly before the current pulse occurs.

The initial voltage $V_C^{(n)}(t=0)$ on the capacitance C is proportional to the voltage on an average capacitance $V_C(t=0)$. The proportional coefficient $k_R^{(n)}$ is the same as for resistances $V_C^{(n)}(t=0) = k_R^{(n)}\cdot V_C(t=0)$ based on earlier assumptions described above.

The consequence is that only four average cell parameters (R_0, R_1, k_I, C) and N relative cell resistances $k_R^{(n)}$ must be determined for the power prediction. Methods for their determination are presented in Section 4.3.

Using above assumptions an optimized algorithm, which requires substantially less computing power than the straight-forward method, can be implemented as follows:

1) For each cell n ($n = 1\ldots N$) the current limits ($I_{\max}^{(n)}, I_{\min}^{(n)}$) based on the battery specification and eventually on present conditions (e.g. temperature) are predefined. The total current limits for the entire battery pack are then calculated:

$$I_{\max} = \min_{n=1\ldots N}\left(I_{\max}^{(n)}\right) \tag{16a}$$

$$I_{\min} = \max_{n=1\ldots N}\left(I_{\min}^{(n)}\right) \tag{16b}$$

2) The cell $N1$ with the highest initial open circuit voltage $V_{OCV}^{\max}(t=0) = \max_{n=1\ldots N}(V_{OCV}^{(n)}(t=0))$ and the cell $N2$ with

the lowest initial open circuit voltage $V_{OCV}^{min}(t=0) = \min_{n=1...N}(V_{OCV}^{(n)}(t=0))$ are selected. These cells are good candidates to be the "weakest" cells regarding available charging and discharging power respectively.

3) For the cell $N1$ the maximum allowable charge current $I_{ch}^{(N1)}$ and for the cell $N2$ the minimum allowable discharge current $I_{disch}^{(N2)}$ are calculated applying the algorithm presented in Section 4.1.
4) The next candidate that may limit the charging and discharging power is the cells $N3$ with the highest relative resistance $k_R^{max} = \max_{n=1...N}(k_R^{(n)})$. The maximum allowable charge current $I_{ch}^{(N3)}$ and the minimum allowable discharge current $I_{disch}^{(N3)}$ are calculated for this cell applying the algorithm presented in Section 4.1. Thereby as the current limits I_{max} and I_{min} the previously calculated currents $I_{ch}^{(N1)}$ and $I_{disch}^{(N2)}$ are used ($I_{max} = I_{ch}^{(N1)};\ I_{min} = I_{disch}^{(N2)}$).
5) Currents $I_{ch}^{(N3)}$ and $I_{disch}^{(N3)}$ calculated in the previous step consider current limits $(I_{max}^{(n)}, I_{min}^{(n)})$ of all cells in the battery pack. Voltage limits of cell $N1$ (with the highest initial OCV), cell $N2$ (with the lowest initial OCV) and cell $N3$ (with the highest relative resistance) are also already taken into account. Additionally to these cells ($N1$, $N2$ and $N3$) further cells with certain combinations of the relative resistance and the OCV might be classified as "weak" as well and therefore limit the available power. For charging such candidates are (group "charge"):
   - all cells with the initial OCV higher than the initial OCV of the cell $N3$ ($V_{OCV}^{(n)}(t=0) > V_{OCV}^{(N3)}(t=0)$) as well as
   - all cells with the relative resistance higher than the relative resistance of the cell $N1$ ($k_R^{(n)} > k_R^{(N1)}$)

   For discharging such candidates are (group "discharge"):
   - all cells with the initial OCV lower than the initial OCV of the cell $N3$ ($V_{OCV}^{(n)}(t=0) < V_{OCV}^{(N3)}(t=0)$) as well as
   - all cells with the relative resistance higher than the relative resistance of the cell $N2$ ($k_R^{(n)} > k_R^{(N2)}$).

   For each cell n ($n = 1...N_{charge}$) in group "charge" the maximum allowable charge current $I_{ch}^{(n)}$ is calculated one after the other applying the algorithm presented in Section 4.1. Thereby the current limit I_{max} is set each time to the maximum allowable charge current $I_{ch}^{(n-1)}$ calculated for the previous cell $n-1$. The resulting current $I_{ch} = I_{ch}^{(Ncharge)}$ is the maximum allowable charge current that considers the current and voltage limits for all individual cells in a battery pack.

   Respectively for each cell n ($n = 1...N_{discharge}$) in group "discharge" the minimum allowable discharge current $I_{disch}^{(n)}$ is calculated one after the other applying the algorithm presented in Section 4.1. Thereby the current limit I_{min} is set to the minimum allowable discharge current $I_{disch}^{(n-1)}$ calculated for the previous cell $n-1$. The resulting current $I_{disch} = I_{disch}^{(Ndischarge)}$ is the minimum allowable discharge current that considers the current and voltage limits for all individual cells in a battery pack.

6) Using calculated currents I_{ch} and I_{disch} the average voltage of all cells at the end of the charge or discharge constant current pulse ($V_{ch}(\Delta t)$ and $V_{disch}(\Delta t)$) can be predicted according to Eq. (3) and using average cell parameters (R_0, R_1, k_I, C). Subsequently the total predicted voltage of the battery pack is:

$$V_{ch}^{pack}(\Delta t) = N \cdot V_{ch}(\Delta t) \tag{17a}$$

$$V_{disch}^{pack}(\Delta t) = N \cdot V_{disch}(\Delta t) \tag{17b}$$

The total predicted power of the battery pack:

$$P_{ch}^{pack}(\Delta t) = I_{ch} \cdot V_{ch}^{pack}(\Delta t) \tag{18a}$$

$$V_{disch}^{pack}(\Delta t) = I_{disch} \cdot V_{disch}^{pack}(\Delta t) \tag{18b}$$

This strategy with the preselection of cells allows reducing the number of calculations and ensures the real-time capability of the algorithm by tolerable inaccuracy.

4.3. On-line calculation of cell parameters required for power prediction

The optimized method for the prediction of the available power presented in Section 4.2.2 requires four average cell parameters (R_0, R_1, k_I, C) and N relative resistances $k_R^{(n)}$ of individual cells connected in series in a battery pack. All these parameters must be calculated on-line to reflect the present conditions of the cells (SoC, SoH, temperature). The respective algorithms are presented in the following.

4.3.1. Calculation of average cell parameters

Average cell parameters (R_0, R_1, k_I, C) are parameters of the equivalent circuit model in Fig. 1 when the current $I(t)$ in this ECM is taken as a total battery pack current and the voltage $V(t)$ is taken as a total battery pack voltage divided by the number of cells connected in series (N): $I(t) = I^{pack}(t)$; $V(t) = V^{pack}(t)/N$. For the determination of these average cell parameters the recursive algorithm described in detail in our previous work [17] is applied. It can be summarized as follows: The combination of certain values of average cell parameters (R_0, R_1, k_I, C) is called "parameter set ($\mathbf{P}$)". For example $\mathbf{P} = \{R_0 = 1\ \text{m}\Omega,\ R_1 = 1\ \text{m}\Omega,\ C = 200\ \text{F}$ and $k_I = 0.01\ \text{A}^{-1}\}$. The battery load profile is divided on-line into short evaluation periods with duration of some 10 s each. At the beginning of each evaluation period S different parameter sets ($\mathbf{P}_1$, $\mathbf{P}_2$, … $\mathbf{P}_S$) are formed and then S battery voltages at each sample step k during this period are calculated using the measured battery current and the ECM in Fig. 1 with these parameter sets. Subsequently, the voltages are compared to the measured battery voltage. The parameter set which results in the lowest estimation error between the measured and the calculated voltage is selected as the best present parameter estimation. This parameter set is used as a basis to form parameter sets for the next evaluation period. It is also used for power prediction.

4.3.2. Calculation of relative cell resistances

The relative cell resistance $k_R^{(n)}$ as defined in Section 4.2 must be calculated individually for each of all N cells connected in series in a battery pack. Since the number of cells might be very large (up to some hundred), a simple, but sufficient algorithm is required. It can be implemented as follows: If the dynamic and the current dependency of all cells are assumed to be equal (see Section 4.2), then each individual cell contribute to the total change of the battery voltage under load proportionally to their relative resistance:

$$\Delta V^{(n)} = k_R^{(n)} \cdot \left(\Delta V^{pack}/N\right) \tag{19}$$

$\Delta V^{(n)}$ is the voltage change of the single cell n; ΔV^{pack} is the voltage change of the total battery pack. These voltage changes can be measured between two sample steps k and $k-1$: $\Delta V^{(n)} = V^{(n)}(k) - V^{(n)}(k-1)$; $\Delta V^{pack} = V^{pack}(k) - V^{pack}(k-1)$.

Therefore, to calculate the relative resistance at each sample step k it is sufficient to measure the total battery pack voltage and individual cell voltages as well as to perform for each cell the following simple calculation:

$$k_R^{(n)}(k) = \Delta V^{(n)}(k) \cdot N / \Delta V^{\mathrm{pack}}(k) \tag{20}$$

In practice the inaccuracy of the voltage measurement as well as the fact that voltages are measured not absolutely synchronal must be considered. A low pass filter can be applied and the calculation can be performed only when the change of the total battery voltage is much higher than the resolution of the voltage measurement:

$$\begin{cases} k_R^{(n)}(k) = k_R^{(n)}(k) \cdot (1 - k_{\mathrm{LP}}) + \Delta V^{(n)}(k) \cdot \frac{N}{\Delta V^{\mathrm{pack}}(k)} \cdot k_{\mathrm{LP}}, & \text{if } \Delta V^{\mathrm{pack}}(k) > \Delta V_{\mathrm{meas,min}} \\ k_R^{(n)}(k) = k_R^{(n)}(k-1) & \text{otherwise} \end{cases} \tag{21}$$

The low pass filter parameter k_{LP} ($0 < k_{\mathrm{LP}} < 1$) and the minimal voltage change $\Delta V_{\mathrm{meas,min}}$ must be chosen considering the typical dynamic of the battery load in a given application and the properties of the measuring system. At the beginning of the calculation the relative cell resistances can be initialized with value 1. Alternatively the previously calculated values can be stored in the non-volatile memory of the BMS and used for initialization.

5. Software-in-the-loop setup for verification tests

In this section a software-in-the-loop setup is described. It is used to verify the optimized algorithm for the prediction of the available power proposed in Section 4.2.2. The setup consists of a real-time computer, a battery test bench system, a measuring system and a device under test (DUT) in a temperature chamber (Fig. 4). As a DUT four 40 Ah lithium-ion cells of type SLPB100216216H manufactured by Kokam are used (Table 1). They are connected in series to a small battery pack. The voltage of each individual cell ($V_1 \ldots V_4$), the total battery pack voltage (V), battery current (I) and the temperature on the surface of the first cell (T) are measured using a measuring system. This measuring system is a part of BMS hardware developed at ISEA. Its characteristics are presented in Table 2. The battery pack under test is placed in a temperature chamber (Binder MK 240). It is also connected to the battery test bench system (Digatron ME) that is used to emulate the battery load. The battery test bench system is controlled by a real-time computer that is used to generate load profile in form of sequence of current values $I(t)$. The algorithm for power prediction is also executed on this real-time computer. The battery test bench system, the measuring system and the real-time computer are interconnected via CAN-bus.

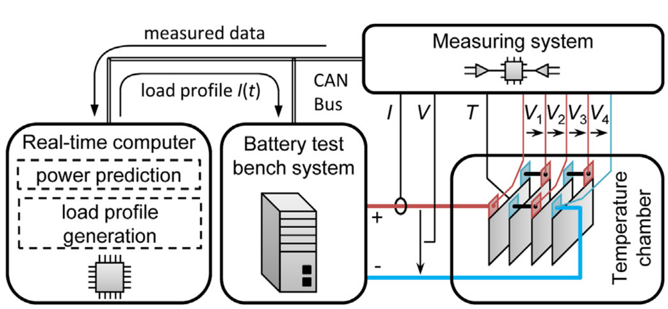

Fig. 4. The software-in-the-loop setup for verification tests.

As a basis for verification tests a battery load profile measured in an electric vehicle prototype during city driving is used. A charging or discharging current pulse with duration Δt is integrated periodically into this profile approximately after each 2.5 min. These pulses are needed to have deterministic points for the verification of power prediction. The strength of the current pulse (I_{ch} or I_{disch}) is calculated on-line applying the proposed power prediction algorithm each time directly before the pulse. The power prediction is accurate if at the end of the charging or discharging current pulse one of two conditions is fulfilled:

1) One of the cell voltages hits the predefined voltage limit ($V_{\max} = 4.2$ V or $V_{\min} = 3.2$ V) and the current is within of predefined current range $I_{\min} < I < I_{\max}$ ($I_{\max} = 160$ A, $I_{\min} = -180$ A).
2) The current is equal to the predefined current limit for given cells ($I_{\mathrm{ch}} = I_{\max}$, $I_{\mathrm{disch}} = I_{\min}$) and all cell voltages $V^{(n)}$ are within of the predefined voltage range $V_{\min} < V^{(n)} < V_{\max}$.

The second case is trivial for the power prediction algorithm. Therefore only the first case is used to qualify the accuracy. As an indicator the deviation ΔV between the maximal (for charging pulse) or minimal (for discharging pulse) cell voltage at the end of the current pulse and the predefined voltage limit ($V_{\max}$ or $V_{\min}$) is used: $\Delta V = \max(V^{(n)}) - V_{\max}$ for charging; $\Delta V = \min(V^{(n)}) - V_{\min}$ for discharging. Unfortunately, the inaccuracy regarding the predicted power cannot be calculated directly because the real available power is not known. Its knowledge would require the knowledge of the current that would lead exactly to the result $\Delta V = 0$, but this current cannot be measured or calculated (if that was possible, we would have an ideal power prediction method). However, the estimation of the real available power is possible: The current pulse causes a voltage drop V_{drop} (by discharging) or voltage rise V_{rise} (by charging) on the battery relatively to its present OCV. The maximal power is achieved if the voltage at the end of the current pulse reaches exactly the predefined voltage limit. The deviation ΔV between both related to the voltage drop or rise is then approximately the relative inaccuracy of the proposed power prediction:

$$E_{\Delta P} = \Delta P / P \approx \Delta V / V_{\mathrm{drop\ (or\ rise)}} \tag{22}$$

When the current in the battery directly before the current pulse is not zero, then the voltage drop or rise cannot be measured. Nevertheless, it can be estimated as $V_{\mathrm{drop(or\ rise)}} = I_{\mathrm{lim}} \cdot (R_0 + R(I_{\mathrm{lim}}))$. Therefore, the inaccuracy of power prediction can be estimated applying Eq. (22) as:

Table 1
Battery cells used for verification tests.

Cell number	Present capacity	SoH	SoC relative to the cell 3
1	42.0 Ah	Slightly aged	−1.0%
2	42.5 Ah	New	−0.5%
3	42.6 Ah	New	–
4	42.2 Ah	New	−2.0%

Table 2
Characteristics of the measuring hardware used for verification tests.

Characteristic	Value
Max. inaccuracy of cell voltage measurement	±5 mV
Max. inaccuracy of pack voltage measurement	±40 mV
Max. inaccuracy of current measurement	±100 mA
Sample rate	100 ms

$$E_{\Delta P} = \Delta V / (I_{\mathrm{lim}} \cdot (R_0 + R(I_{\mathrm{lim}}))) \qquad (23)$$

It is worth to point out that this definition is different than the absolute ΔV or the relative $\Delta V/V_{\mathrm{cell}}$ inaccuracy of the modeled cell voltage that is used by some other authors [9,12,14] to verify power prediction algorithms. The proposed estimation of the inaccuracy reflects better the real inaccuracy but leads to higher values than a relative inaccuracy of the modeled cell voltage $\Delta V/V_{\mathrm{cell}}$ because in most cases $V_{\mathrm{cell}} \gg |V_{\mathrm{drop(or\ rise)}}|$.

6. Verification tests and discussion

The first test is carried out to verify the prediction of the available power by charging the battery. For the demonstration purpose the battery pack consists of four cells as described in Section 5. It has been charged ($SoC_{cell1} = 99\%$; $SoC_{cell2} = 99.5\%$; $SoC_{cell3} = 100\%$; $SoC_{cell4} = 98\%$) and tempered to 10 °C before the test is carried out. During the test the load profile with integrated constant current

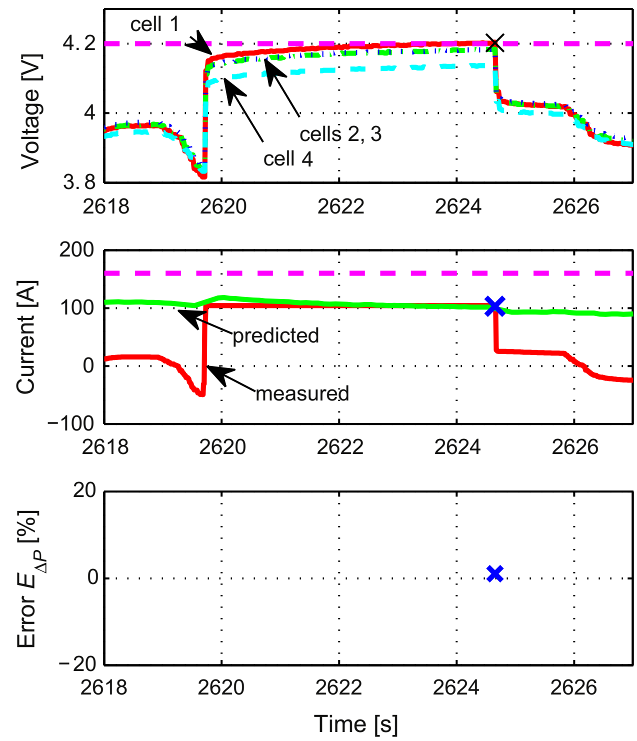

Fig. 6. Detailed representation of the current pulse shown in Fig. 5 at $t = 2620$ s.

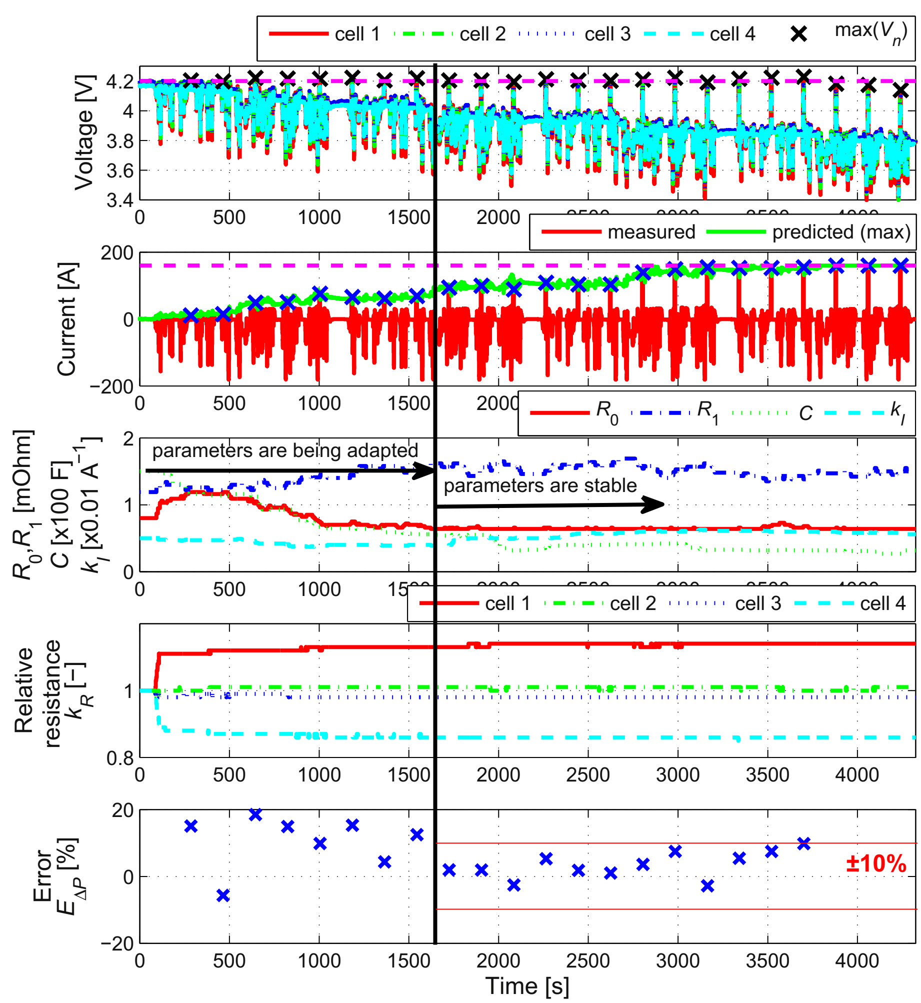

Fig. 5. Results of the verification test.

charge pulses (pulse duration $\Delta t = 5$ s), as described in previous Section 5, is applied. The results are shown in Fig. 5 and the imposed current pulse at $t = 2620$ s is shown in detail in Fig. 6. At the beginning of the test the battery parameters (R_0, R_1, C, k_I, $k_R(1\ldots4)$) were initialized with values that are incorrect for the given cell. The intention was to demonstrate the adaption capability of the algorithm. During the first 1600 seconds the parameter adaption is still in progress. Therefore, the inaccuracy of the power prediction is high. After the model parameters are adapted to the battery characteristics, the inaccuracy of power prediction calculated according to Eq. (23) is within $\pm10\%$ with a root-mean-square error (RMSE) of approximately 5%.

The current amplitude for the last three current pulses is limited not by the voltage but by the predefined current limit $I_{\max} = 160$ A. This is a trivial case for power prediction, as described above, and therefore excluded from the calculation of the error value.

As can be seen the algorithm succeeds in the determination of the relative cell resistances. The relative resistance of the first cell is higher because this cell is aged (Table 1). The lower relative resistance of cell 4 can be explained considering the measurement of cell voltages. The voltages of cells 1, 2 and 3 are measured between their positive terminal and the positive terminal of the next cell. Therefore their relative resistances include additionally resistances of cell connectors. In contrast, the voltage on cell 4 is measured directly between its positive and negative terminal and therefore do not include the voltage drop on the cell connector under load. As a result, the relative resistance of cell 4 is identified being lower than the relative resistance of cells 2 and 3, even though all these three cells are new.

The results of the similar test, but with integrated discharging current pulses for the verification of the predicted available discharging power, are shown in Fig. 7. The battery has been charged ($SoC_{cell1} = 39\%$; $SoC_{cell2} = 39.5\%$; $SoC_{cell3} = 40\%$; $SoC_{cell4} = 38\%$) and tempered to 10 °C before the test is carried out. During the test the load profile with integrated constant current discharge pulses (pulse duration $\Delta t = 5$ s), as described in previous Section 5, is applied. The results show that the inaccuracy of power prediction is higher in this case than by charging the battery, especially at very low SoC. The reason is that at SoC below about 30% the diffusion overvoltage by charging or discharging the battery rises (especially extremely at SoC lower than about 15%), but it is not considered in the used battery model (Fig. 1). The change of other battery parameters at low SoC as the increase of the charge transfer resistance (R_1) and the increase of the relative resistance k_R of the most discharged cell 4 are tracked exactly by the algorithm.

These results as well as results of other tests are summarized in Table 3. They show that the proposed method overestimates the available power for longer forecast periods (for $\Delta t = 5$ s and $\Delta t = 10$ s) because the mean relative error is positive for charging and is negative for discharging. The reason is the same as the high

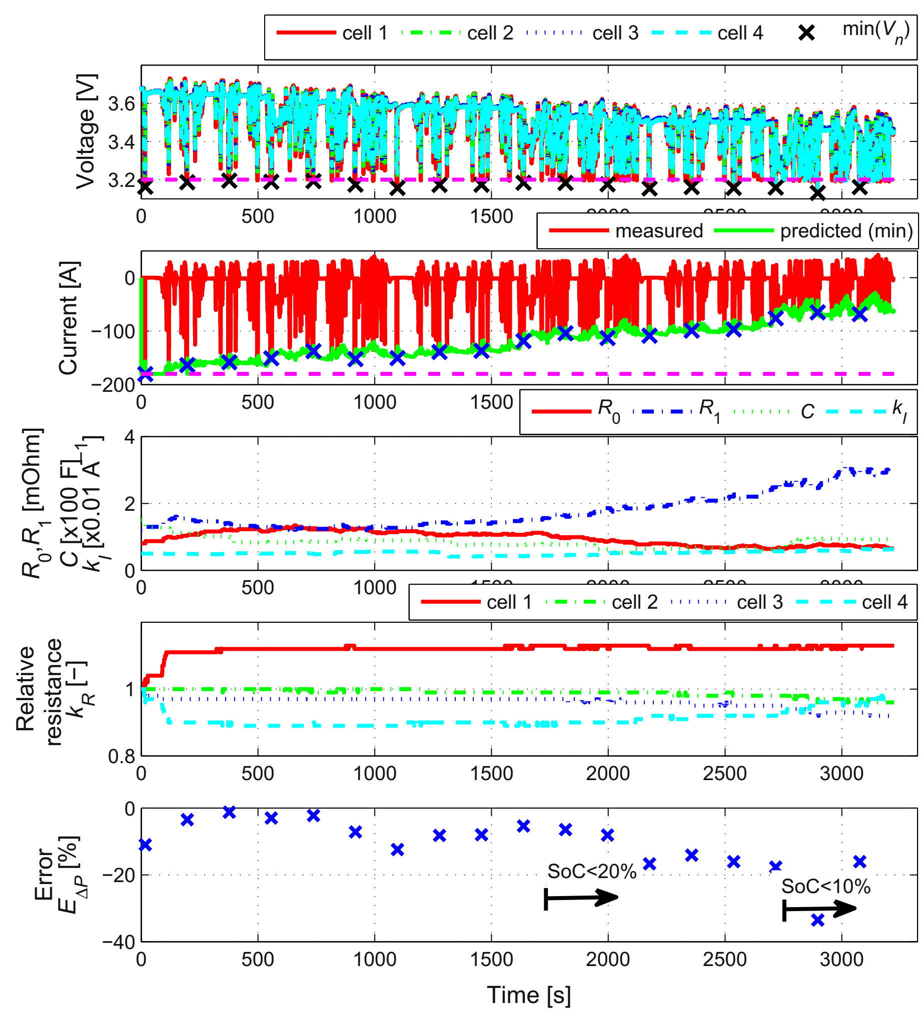

Fig. 7. Results of the verification test.

Table 3
The inaccuracy of the proposed method for different reference cases. The relative error $E_{\Delta P}$ is calculated for each constant current or constant power event according to Eq. (23). All tests are performed at 10 °C.

Pulse type	Charging/ discharging	Duration of the pulse Δt	RMSE of power prediction, RMSE($E_{\Delta P}$)	Mean relative error, mean($E_{\Delta P}$)
Constant current	Charging	1 s	4.1%	−2.3%
		5 s	5.0%	3.4%
		10 s	9.7%	9.0%
	Discharging	1 s	6.5%	1.4%
		5 s	14.4%	−12.3%
		10 s	19.4%	−18.0%
Constant power	Charging	5 s	5.3%	3.5%
	Discharging	5 s	12.3%	−11.4%

inaccuracy at low SoC: an additional diffusion overvoltage is not considered. For a new cell the diffusion can be additionally taken into account as for example done in Ref. [13]. However this method does not allow adaption of the diffusion parameters to the battery SoH. Therefore, another adaptive algorithm for consideration of the diffusion overvoltage is required and will be presented in our future work.

Until now a reference case of charging or discharging the battery with constant current is considered for power prediction. The results of two tests with a constant power pulse instead of the constant current pulse are presented in Table 3. The available power is calculated as for the reference case of constant current charging or discharging. Therefore, it is theoretically is not correct for the constant power pulse. Nevertheless the results show sufficient accuracy. The explicit consideration of the constant power case by prediction of the available power would require high computing power. The reason is that in this case the change of the battery current I during the power pulse and therefore the change of the charge transfer resistance $R(I)$ must be considered. The constant current method applied for constant power pulse neglects this change, which is actually small, and therefore leads to rather low influence on the overall error.

Is the achieved accuracy of the proposed method good or not? The inaccuracy of 5% calculated as defined above (Eq. (23)) means for the given cell type at 10 °C that the voltage of each single cell must be modeled with maximal inaccuracy of about 5–20 mV (0.5–0.1% related to the cell voltage) to achieve this value. Such inaccuracy is very challenging even for complex battery models. Furthermore, it is comparable with the inaccuracy of the measuring hardware typically used in BMS. Therefore, the inaccuracy of 5% for power prediction is very positively and even higher values up to 10–15% can also be considered as sufficient in performance.

Unfortunately other authors do not provide the exact information about the accuracy of their algorithms and show only verification tests carried out at room temperature, where the power prediction is not that challenging as at lower temperatures. Therefore, an accurate comparison with alternative methods presented in other publications is not possible. In Ref. [9] only the comparison between results from different methods is given, but no reference values are provided. In Refs. [12,14] additionally the deviation between the modeled and the measured cell voltage is given. It varies in the range of −26 to 49 mV and −30 to 20 mV respectively. In Ref. [13] a reference case of constant voltage charging or discharging is used. Plots presented in that work show that the error between the predicted and the measured available power is up to 20% in some cases.

From these considerations it can be concluded that the method proposed in this work is at least as accurate as other methods at room temperature. At lower temperatures it is most likely significantly accurate than other methods because of the considered current dependency of battery resistance.

The last aspect that has to be discussed is the real-time capability of the proposed method. The optimized algorithm for power prediction (Section 4.2.2) including algorithms for on-line determination of battery parameters (Section 4.3) has been implemented on a low-cost 16 bit microcontroller (Infineon XC2287). It has been running with simulated data of 30 cells connected in series. The processor load amounted to about 60%, which is already a good result. A further optimization and usage of slightly powerful 32 bit microcontroller will be sufficient to run the algorithm for a battery pack consisting of up to some hundred cells.

7. Conclusion

In this work a new method for the prediction of the available power of lithium-ion battery is presented. The key characteristics of the approach are:

- consideration of differences between characteristics of individual cells in a battery pack;
- explicit consideration of current dependency of battery resistance that ensures an accurate power prediction at lower temperatures;
- the parameters of the battery model used by the algorithm are fully adaptable on-line to the present state of the battery (SoC, SoH, temperature);
- real-time capability is ensured by optimization regarding computing power and memory consumption.

The proposed method shows promising results. The inaccuracy depends strongly on the forecast period. For longer prediction times, especially at lower SoC, an additional consideration of the battery diffusion overvoltage is required and will be presented in our next work.

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